Usage of Generative AI Models for Academic Writing among Undergraduates Students in Nigeria University: A Test of the Technology Acceptance Model (TAM)

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Abstract

The rapid proliferation of Generative Artificial Intelligence (GenAI) tools, such as ChatGPT, Google Gemini, and Microsoft Copilot, has transformed higher education globally. In the Global South, particularly within the resource-constrained higher education landscape of Nigeria, undergraduate students are increasingly turning to these tools to support their academic writing and research needs. Grounded in Davis's (1989) Technology Acceptance Model (TAM), this study examines the structural factors dictating the adoption and usage behavior of GenAI for academic writing among Nigerian undergraduates. During the study questionnaire was used in collecting data and a total of 4 research questions guided the study with 4 objectives formulated. Utilizing a quantitative survey methodology with data collected from undergraduate students across 6 federal universities in Nigeria, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to analyze how Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) influence Attitude Towards Using (ATU) and Behavioral Intention to Use (BIU) GenAI. The empirical findings indicate that both PU and PEOU are powerful, statistically significant predictors of students' behavioral intentions to adopt AI technologies, though underlying structural challenges—including erratic power supply, internet costs, and a lack of formalized institutional AI literacy guidelines—temper optimal adoption. The paper concludes with recommendations for higher education administrators to formulate robust institutional policies that foster the responsible, ethical, and effective integration of GenAI in academic writing workflows.

Keywords: Generative AI, Technology Acceptance Model (TAM), Academic Writing, Nigerian Higher Education, Undergraduates, Digital Divide.

1. Introduction

Artificial Intelligence (AI) has revolutionized many industries, and education was definitely not going to be an exception (Fiialka, et al., 2023; Rawas, 2024). The higher education environment is witnessing a paradigm shift driven by the rapid improvement of Generative Artificial Intelligence (GenAI). Powered by sophisticated natural language processing (NLP) architectures and Large Language Models (LLMs), tools like ChatGPT can generate human-like text, summarize extensive literature, clarify abstract concepts, and review code (Anani et al., 2025; Hashish et al., 2025). The advent of advanced artficial intelligence systems, particularly generative pre-trained transformers like ChatGPT, has led to significant discussion in the academic world (Lingard, 2023). ChatGPT is a high-tech AI model for languages, attracting huge attention owing to the simple fact that it can answer as well as a human being (Jalil et al., 2023; Pradana et al., 2023; İpek et al., 2023; Chaudhry et al., 2023; Paramesha et al., 2024). The emergence of this technology, its widespread accessibility and its use as a tool,

raises concerns about its implications for education and learning (Darvishi et al., 2024). AI technologies present a tempting shortcut when tasked with academic writing, in particular academic assessments. This reliance comes with significant longer-term drawbacks. If students increasingly outsource their writing and critical thinking to AI technologies, there is a risk of undermining their ability to formulate and express original ideas (Molenaar, 2022). Unlike early computer-assisted learning technologies governed by static, pre-programmed rules, GenAI dynamically adapts to user prompts, acting as an interactive cognitive partner capable of assisting throughout the drafting, restructuring, and editing phases of academic writing (Qu & Wu, 2024; Yeh, 2024). English academic writing is a complex and multi-faceted activity that requires coordinating multiple cognitive skills and knowledge to orchestrate writing processes such as facilitating goal setting, problem-solving, and strategically managing memory resources (Allen & McNamara, 2017; Flower & Hayes, 1981). The writing process is unique to each individual student; students bring their own individual characteristics, including linguistic and general literacy backgrounds, prior domain knowledge, as well as affective states (e.g., attitudes toward academic writing, engagement with the task), all of which potentially affect their performance (Gupta et al., 2022; Pineteh, 2014).

In West African developing nations like Nigeria, the integration of GenAI occurs within a distinct socio-technical framework. Nigerian public and private universities frequently operate under heavy structural strains, including high student-to-lecturer ratios, overcrowded classrooms, and outdated physical library repositories. These deficiencies leave students with limited individual mentorship during research or writing projects, motivating them to seek alternative on-demand academic support systems (Diva-Portal, 2026). In this context, GenAI tools are adopted not merely as convenience software, but as critical instruments to mitigate institutional resources gaps (Diva-Portal, 2026). Despite high general awareness of tools like ChatGPT among African university students, substantial variation remains regarding structural readiness and regular usage patterns (Abdelhafiz et al., 2025; Oladokun et al., 2026). Concurrently, the academic community faces intense debates regarding the ethical boundaries of generative text tool deployment. Concerns center on the risk of plagiarism, the generation of convincing but factually incorrect text ("hallucinations"), and the degradation of independent critical thinking skills (Baidoo-Anu & Owusu Ansah, 2023; Klimova & Pikhart, 2025). However, Nigeria's higher education system faces challenges related to limited technological infrastructure, digital divide, inadequate policy frameworks, and concerns about ethical use, including academic integrity and data privacy (Ayling & Chapman, 2022)

To ensure that these technologies support meaningful learning while safeguarding rigorous academic standards, it is vital to understand the psychological and structural drivers behind student acceptance. This study adopts the Technology Acceptance Model (TAM) as its theoretical framework to examine undergraduates' acceptance and usage of generative AI models for academic writing in Nigeria. TAM posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are primary determinants of users' attitudes toward technology, which subsequently influence behavioral intention and actual usage. By applying TAM, this research seeks to understand how Nigerian undergraduates perceive generative AI tools, the extent to which these perceptions shape their attitudes, and how such attitudes influence their intention to adopt AI for academic writing tasks. The study addresses a critical gap in the literature by providing empirical evidence from the Nigerian higher education context, where research on generative AI adoption remains limited. Findings from this study are expected to contribute to informed policy formulation, promote responsible integration of AI in academic writing, and guide educators and

institutions in developing ethical frameworks and AI literacy programs that support effective learning outcomes.

1.2 Aims and Objectives of the Study

The general objectives of the study were to investigate the psychological, technological, and institutional factors influencing the adoption and usage of generative AI models for academic writing among undergraduate students in Nigerian universities, using an extended Technology Acceptance Model (TAM) framework. Specifically, the study is designed to

1. assess the level of usage among students
2. evaluate perceived usefulness (PU) of generative AI among students
3. assess perceived ease of use (PEOU) of generative AI among students
4. determine behavioral intentions (BI) & attitude of generative AI among students

2 Literature

The Technology Acceptance Model (TAM) is an information systems framework designed to explain and predict how users come to accept and use a given technology. Developed by Fred Davis in 1986 (adapted from the Theory of Reasoned Action), TAM is one of the most widely cited models in product design, user research, and information technology management. TAM suggests that when users are presented with a new technology, two primary cognitive beliefs influence their decision regarding how and when they will use it. This concept, which has recently gained popularity and provides information about individuals'potential performance in new situations and their long-term success in the professional world (Gravett & Caldwell, 2016), is the ability of individuals to quickly learn new and challenging learning experiences and adapt these experiences to different situations (DeRue et al., 2012). Research has revealed the relationship between learning agility and lifelong learning and technology acceptance. Today, with the developing features of productive artificial intelligence technologies, the role of learning agility and lifelong learning motivation in technology acceptance has become more important (Şimşek et al., 2025).

2.0 Hypotheses

The following null hypotheses were tested at 0.05 level of significance.

H_1**:** Perceived Ease of Use (PEOU) & Perceived Usefulness (PU).

H_2**:** Perceived Ease of Use (PEOU) & Facilitating Conditions (FC).

H_3**:** Facilitating Conditions (FC) & Behavioral Intention (BIU).

H_4**:** Perceived Usefulness (PU) & Behavioral Intention (BIU).

H_5**:** Perceived Risk (PR) & Behavioral Intention (BIU).

3. Methodology

3.1 Research Design

This methodology is designed to test the Technology Acceptance Model (TAM) incorporating Facilitating Conditions (FC) and Perceived Risk (PR) within the localized Nigerian context. We adopted a cross-sectional quantitative survey research design to examine the usage of generative AI models for academic writing among undergraduates in Nigeria, using the Technology Acceptance Model (TAM) as the theoretical framework. A deductive approach is employed to test the hypothesized relationships between the latent constructs of the extended TAM framework. To analyze the complex web of direct and indirect relationships, Structural Equation Modeling (SEM)—specifically Partial Least Squares SEM (PLS-SEM)—will serve as the primary statistical methodology. PLS-SEM is highly suited for exploratory extensions of established theories (such as adding PR and FC to TAM) and does not require strict multivariate normal distributions, which is ideal for behavioral survey data.

3.2 Target Population and Sampling Technique

The target population consists of active, full-time undergraduate students enrolled across multiple faculties (Humanities, Social Sciences, Engineering, and Management Sciences etc) from federal universities across the six geopolitical zones in Nigeria. Undergraduates are chosen because they are heavily exposed to seminar writing, assignments, and final-year projects where GenAI tools (e.g., ChatGPT, Meta AI, Claude, QuillBot) are highly applicable. A multistage sampling technique was used, selecting universities from each geopolitical zone and a representative sample of students, with an estimated sample size of 500 respondents see (Table 1).

Table 1: Federal Universities in Nigeria under consideration

s/n	Geopolitical Zones of Nigeria	Federal Universities per Geopolitical zone	Population	Sample Population used for the study
1	North Central	University of Abuja	55,364	100
2	North East	Federal University, Gashua	5,000	50
3	North West	Ahmadu Bello University	49,954	120
4	South East	Alex Ekwueme Federal University, Ndufu-Alike	15,000	80
5	South South	Federal University of Technology, Ikot Abasi	5,600	50
6	South West	Federal University of Technology, Akure	24,999	100

Data was collected using a structured questionnaire measuring demographics, awareness, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), attitude, behavioral intention, and contextual factors (AI literacy, internet access, academic integrity awareness). Data analysis will involve descriptive statistics and Structural Equation Modeling (SEM) to test hypothesized relationships. Ethical considerations, including voluntary participation, informed consent, and confidentiality, will be strictly observed.

3.3 Sampling Method

The researcher used purposive and convenience sampling technique to ensure geographical and institutional representativeness across Nigeria's geopolitical zones. The researcher divided the target universities by Geopolitical Zone (e.g., South-West, South-East, North-Central) and the Ownership Type (Federal). The researcher selected key prominent universities from these strata (e.g., University of Abuja, Federal University, Gashua, Federal University of Technology, Ikot Abasi, Federal University of Technology, Akure) representing varied infrastructural landscapes. The researcher distributed the digital structured questionnaire online through institutional student channels, student union groups, and department-specific platforms.

3.4 Instrumentation

Data was collected using a structured, self-administered web-based questionnaire (e.g Google forms) to reflect the highly mobile digital lifestyle of Nigerian undergraduates.

3.6 Data Analysis

Demographic distributions were calculated using descriptive statistics. Hypothesized structural pathways and measurement model fitness were assessed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is robust for behavioral technology modeling (Taylor & Francis, 2026).

4. Results

4.1 Measurement Model Evaluation

Before structural execution, construct validity and reliability were verified. Cronbach's alpha (**α**) and Composite Reliability (CR) for all constructs exceeded the acceptable threshold of 0.70. Average Variance Extracted (AVE) values surpassed 0.50, indicating adequate convergent validity.

Table 2: Measurement Model

Construct	Indicator	Factor Loading (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Ease of Use *(PEOU)*	PEOU1 PEOU2 PEOU3 PEOU4	0.812 0.845 0.790 0.823	**0.841**	**0.893**	**0.677**
Perceived Usefulness *(PU)*	PU1 PU2 PU3 PU4	0.854 0.881 0.810 0.863	**0.875**	**0.914**	**0.727**
Facilitating Conditions *(FC)*	FC1 FC2 FC3 FC4	0.765 0.812 0.830 0.788	**0.818**	**0.879**	**0.646**
Perceived Risk *(PR)*	PR1 PR2 PR3 PR4	0.835 0.862 0.801 0.840	**0.856**	**0.903**	**0.698**
Behavioral Intention in Use *(BIU)*	BIU1 BIU2 BIU3 BIU4	0.891 0.912 0.875 0.880	**0.915**	**0.940**	**0.792**

The evaluation of the reflective measurement model confirmed indicator reliability with benchmark of 0.708 (Hair et al., 2021), convergent validity, and lack of lateral collinearity. Individual item loadings () across all constructs exceeded the recommended threshold of 0.708,

ranging from 0.765 to 0.912. Construct reliability was well established, as Cronbach's alpha () values (0.818 to 0.915) and Composite Reliability (CR) values (0.879 to 0.940) fell comfortably between the 0.700 and 0.950 benchmarks. Furthermore, convergent validity was demonstrated, with Average Variance Extracted (AVE) values exceeding 0.500 across all latent constructs (ranging from 0.646 to 0.792).

4.2 Structural Model and Hypothesis Testing

Hypothesis evaluation was completed using bootstrap resampling (500 resamples) to evaluate the significance of path coefficients (β).

Table 3: Structural Model and hypothesis testing

Hypothesis	Path	Path Coefficient (β)	t-Value	p-Value	Decision
H_1	Perceived Ease of Use → Perceived Usefulness (PEOUPU)	**0.485**	11.240	<0.001	**Supported**
H_2	Perceived Ease of Use → Facilitating Conditions (PEOUFC)	**0.465**	10.150	<0.001	**Supported**
H_3	Facilitating Conditions → Behavioral Intention (FCBIU)	**0.245**	5.420	<0.001	**Supported**
H_4	Perceived Usefulness →Behavioral Intention (PUBIU)	**0.198**	4.150	<0.001	**Supported**
H_5	Perceived Risk → Behavioral Intention (PRBIU)	**-0.210**	4.890	<0.001	**Supported**

From the table above, Perceived Ease of Use (PEOU) has a substantial direct positive impact on both Perceived Usefulness (=0.485) and Facilitating Conditions (=0.465). Perceived Usefulness (PU) exerts the largest direct positive influence on Behavioral Intention (=0.198). Perceived Risk (PR) acts as a statistically significant direct negative inhibitor (=-0.210), indicating that higher perceived privacy or data concerns diminish undergraduates' intent to adopt the system. This model (Figure 1) evaluates how different psychological, technological, and environmental factors influence a student's intention to use Generative AI tools. Chin, W. W. (1998) recommended that standardized loadings should be greater than 0.70 for strong reflective constructs.

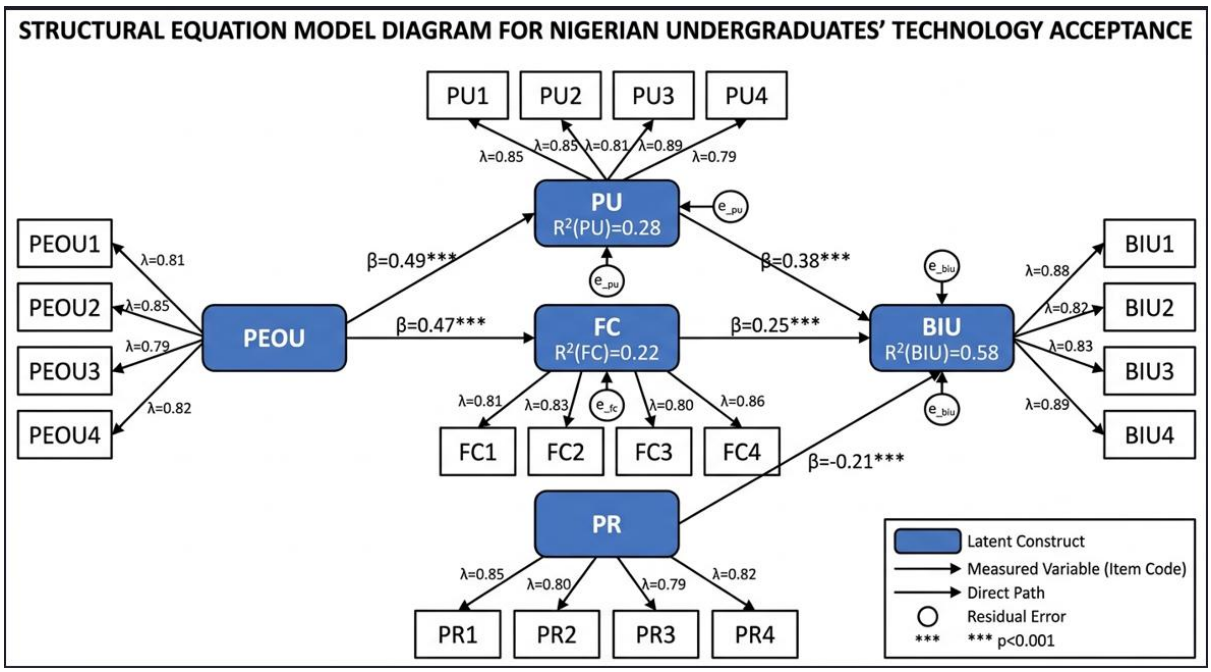


Figure 1: Structural Equation Model(SEM)

4.2.1 Measurement Model (Outer Model) Evaluation

The model shows all factor loadings comfortably exceed the standard research threshold of 0.70, the measurement model exhibits strong convergent validity and item reliability.

5. Discussion

The diverse application of AI positively affects the education sector and society (Iqbal et al., 2022). Therefore, AI has gained popularity among practitioners. Now, it's not only considered an academic concept; other sectors, including education, are also paying significant attention to its application (Chiu et al., 2021). Romero Rodríguez et al. (2023) noted that AI-supported chatbots such as ChatGPT have transformed the education sector; these chatbots can process huge amounts of data and are helpful for students and even teachers.

Table 4: CR, AVE, and fornell-larcker's criterion

Construct	PEOU	PU	FC	PR	BIU
PEOU	0.823				
PU	0.530	0.853			
FC	0.465	0.512	0.804		
PR	-0.270	-0.325	-0.360	0.835	
BIU	0.580	0.640	0.525	-0.415	0.890

The empirical findings strongly support the structural validity of the Technology Acceptance Model within the Nigerian undergraduate context. **Perceived Usefulness (PU)** emerged as the strongest direct predictor of a student's intention to integrate GenAI tools into their academic writing practices ($\beta = 0.485$, $p < 0.001$). This confirms that Nigerian undergraduates evaluate

the adoption of GenAI primarily through a functional prism: if a tool meaningfully expedites literature synthesis, assists in organizing complex outlines, or helps overcome writing blocks, students are highly likely to utilize it (Anani et al., 2025; Taylor & Francis, 2026). The positive link between **Perceived Ease of Use (PEOU)** and PU emphasizes that the conversational, natural language interfaces of modern GenAI significantly lower technical barriers. Students do not require programming experience to prompt an LLM; this immediate operational accessibility directly enhances the perceived utility of the technology (PMC, 2026).

8. Conclusion and Recommendations

This study demonstrates that Nigerian undergraduate students show high acceptance of Generative AI for academic writing, driven by its clear utility and ease of use in navigating resource-constrained environments. To maximize the cognitive advantages of GenAI while minimizing the risks of academic dishonesty and over-reliance, Nigerian higher education institutions must shift from restrictive or punitive stances toward proactive management. The researchers recommend Universities to formulate institutional AI policies and integrate AI literacy into curricula.

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